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Procedia Engineering 81 (2014) 1023 – 1028

Procedia Engineering

www.elsevier.com/locate/procedia

11th International Conference on Technology of Plasticity, ICTP 2014, 19-24 October 2014, Nagoya Congress Center, Nagoya, Japan

# Design optimization of sheet metal stamped parts by CAE simulation and back-propagation neural network

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**Abstract**

The structure stiffness of a certain chassis of an air-conditioner machine is simulated by CAE software. According to the simulation results, combined with orthogonal experiments and BP neural network, the structure design parameters are optimized. Afterwards, numerical simulation of the stamping process is carried out by Dynaform5.7 software to predict the forming quality for the optimized design. Experiments show that the design scheme based on CAE simulation and back-propagation(BP) neural network can not only effectively improve the product's structure stiffness, but also has good forming quality without the defects occurrence such as crack or wrinkle. Furthermore, the deformation is uniform and the dimensional accuracy meets the industry requirement.


Selection and peer-review under responsibility of the Department of Materials Science and Engineering, Nagoya University

*Keyword*: Design optimization; Stamping process; Back-propagation(BP) neural network; CAE simulation; Orthogonal experiment

## 1. Introduction

Chassis is one of the important load-bearing part of outdoor unit of an air-conditioner, whose structure stiffness has a great effect on the total stiffness of air-conditioner machine. If the stiffness of the chassis is insufficient, it may lead to too large vibration during the operation process of air-conditioner machine to cause great noise. Besides, it may result in excessive stress of the pipeline system of air-conditioner machine due to large vibration, which may lead to the fracture of the pipeline system [1, 2].

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Selection and peer-review under responsibility of the Department of Materials Science and Engineering, Nagoya University
doi:10.1016/j.proeng.2014.10.135

A certain chassis of an air-conditioner machine is taken for the research object. Although the structure stiffness of the chassis is affected by various factors such as geometrical parameters, material property, thickness of sheet metal, etc., only geometrical parameters are considered for simplification. Structure stiffness of the initial design scheme is calculated by the finite element analysis software of UG/NX Nastran. The geometrical parameters including die radius, rib height and rib width are regarded as the design variables to be optimized. To avoid the blindness of CAE simulation, orthogonal experiment is used to arrange the minimum simulation times. Furthermore, on account of the powerful function mapping ability of BP neural network, it is introduced to establish the mathematical model between design variables and structure stiffness. In this way, the optimized design scheme can be obtained by integration of CAE simulation, orthogonal experiment and BP neural network. In order to analyze the forming quality of the optimized design scheme, Dynaform5.7 software is applied to simulate the stamping process, the results show that the optimized design scheme has good forming quality without the occurrence of wrinkling or defects.

The method by fusion of finite element method, orthogonal experiment and artificial intelligence technology has a great significance on design optimization, improvement of product's quality and reduction of the mold development cycle, thus it provides a wide application prospect.

## 2. Structure design optimization

### *2.1. Finite element simulation for initial design scheme*

It is known that structure stiffness of the chassis is closely related to material's deformation, and the more deformation is, the less structure stiffness becomes. The deformation of the chassis is mainly caused by the gravity loads of compressor, gas-liquid separator and etc., which is calculated by UG/Nastran software for the initial design scheme. Considering that the deformation of the chassis' flange is very small, so it can be be ignored and the fixed constraints are imposed here. The main gravity loads are denoted as shown in Fig. 1. The material is DX52 steel with the yield strength of 290 MPa, the elastic modulus $E$ of 2.07E8 and the poisson's ratio of 0.28. It is used in sheet forming with anisotropic property, which exerts an evident influence on the formability. The material model of Barlat's-3 parameter plasticity is adopted, whose exponent face of $m$ is 6.0, and the lankford parameters of $R_0$, $R_{45}$, and $R_{90}$ are 1.66, 1.23 and 2.1, respectively. The thickness of sheet metal is 1.2 mm, and the element type is quadrilateral.

The cloud chart of the deformation for initial design scheme is shown in Fig. 2. The maximum deformation is 2.036 mm, whose position is near the location of the maximum gravity load of the compressor. It is so large that the structure stiffness exceeds the industry demand, thus design optimization should be carried out to reduce the maximum value of deformation.

The geometrical parameters such as die radius, rib height and rib width near the location of the maximum deformation are regarded as the design variables. If each design variable has 4 levels, there are simulation times of $4^3$=64, which require a lot of CPU time. In view of that BP neural network has a powerful mapping ability of nonlinear function, prediction is carried out for new data sets after training the sample data sets [3, 4].

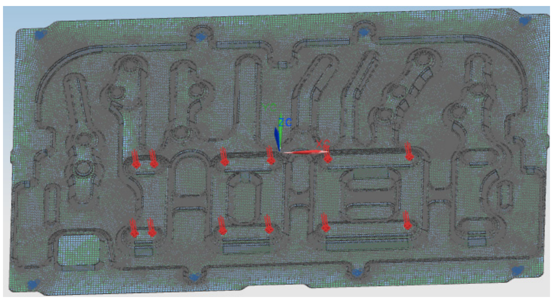

Fig.1. Finite element model for initial design scheme.

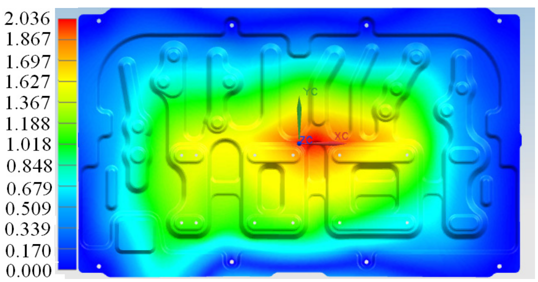


Fig.2. Cloud chart of the deformation for initial design scheme.

### 2.2. Establishment of BP neural network model

It is necessary to establish the function relationship between the geometric parameters and structure stiffness that is expressed by the largest value of deformation. The fillet radius, rib height and rib width at the place near the largest deformation are regarded as the design variables to be optimized, and the minimum value of the largest deformation is accounted as the goal $g_i$ for optimization. In BP neural network model, the input layer has three neurons including the fillet radius $R_i$, rib height $H_i$ and rib width $B_i$, and the hidden layer consists of 10 neurons. There is one neuron in the output layer. Tansig transfer function is adopted between the input layer and the hidden layer. Purelin linear function is used between the hidden layer and the output layer. During the process of training neural network model, the parameters' expected error goal is 1.0E-3, and the learning rate is 0.05. The neural network model is as indicated in Fig. 3.

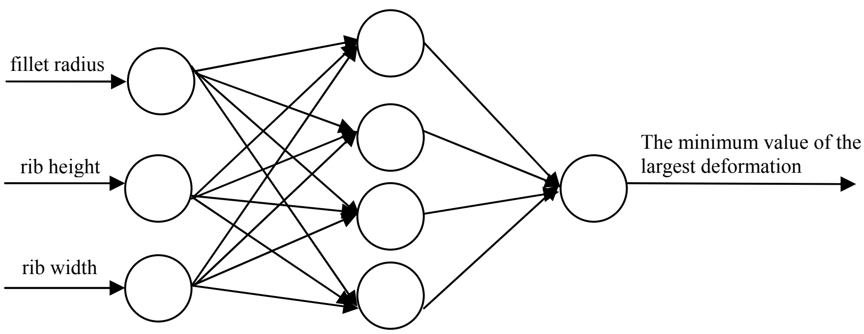


Fig.3. BP neural network model.

### 2.3. Training and prediction of neural network

The distribution and number of training samples have very important influence on the performance of neural network model. In consequence, how to design the experiment plan with various factors and how to choose the reasonable experiment method are the crucial problems that should be considered for BP neural network model. The orthogonal experiment method has the characteristics of equilibrium dispersion and tidy comparability, and it can reflect the overall situation with fewer tests [5,6]. Therefore, the distribution of training samples is determined by orthogonal experiment method.

In the neural network model, there are three design variables of $R_i$, $H_i$ and $B_i$, which are seen as one set of $t_i=\{R_i, H_i, B_i\}$, and the goal value is $g_i$. If every design variable has 4 levels, then the orthogonal experiment table of $L_{16}(4^3)$ is chosen, and training samples are determined with 16 sets of data as seen in Table 1. Compared with the comprehensive test, it requires simulation times of $4^3$=64, hence, great CPU calculation time can be saved.

Table 1. Factors and levels of training samples. unit:mm

| $t_i$ | $R_i$ (mm) | $H_i$(mm) | $B_i$(mm) | $t_i$ | $R_i$ (mm) | $H_i$(mm) | $B_i$ (mm) |
|---|---|---|---|---|---|---|---|
| t1 | 2 | 6 | 30 | t9 | 8 | 6 | 50 |
| t2 | 2 | 9 | 40 | t10 | 8 | 9 | 60 |
| t3 | 2 | 12 | 50 | t11 | 8 | 12 | 30 |
| t4 | 2 | 15 | 60 | t12 | 8 | 15 | 40 |
| t5 | 5 | 6 | 40 | t13 | 11 | 6 | 60 |
| t6 | 5 | 9 | 30 | t14 | 11 | 9 | 50 |
| t7 | 5 | 12 | 60 | t15 | 11 | 12 | 40 |
| t8 | 5 | 15 | 50 | t16 | 11 | 15 | 30 |

After 161 iterations, the system error meets the requirement. Using the trained network model, 6 entirely new sets of test data are forecast. From Table 2, it is seen that the errors between the numerical simulation results and the network predicted results of test data are almost within 10%, hence the neural network model is proved to be reliable.

Table 2. Errors between the simulation results and the neural network predicted results of test data (%).

| No. | $R_i$ (mm) | $H_i$(mm) | $B_i$(mm) | Simulation results(mm) | Predicted results(mm) | Error |
|---|---|---|---|---|---|---|
| 1 | 4 | 14 | 35 | 2.253 | 2.113 | 6.63% |
| 2 | 4 | 14 | 45 | 2.16 | 1.91 | 11.6% |
| 3 | 7 | 10 | 45 | 2.071 | 2.146 | 3.62% |
| 4 | 7 | 10 | 55 | 2.004 | 2.191 | 9.33% |
| 5 | 9 | 8 | 35 | 1.54 | 1.76 | 7.79% |
| 6 | 9 | 8 | 45 | 1.98 | 1.87 | 5.56% |

## *2.4. Determination of the optimization design*

The comprehensive test data of $4^3$=64 with three design variables and four levels for each design variable, and 48 sets of new data are predicted except 16 sets of training data. According to the convergence results, the optimized data set $t_{\mathrm{i}}=\{R_i, H_i, B_i\}$ of design variables is $t_{37}=\{11, 6, 30\}$, and the predicted maximum deformation is 1.62mm. The simulated deformation result for the optimized design scheme is indicated in Fig. 4, from which it is seen that the largest deformation is 1.648mm. The error between the simulation result and the predicted result is 4.65%, which meets the accuracy requirement. In comparison to the initial design, the maximum value of deformation for the optimized design reduces 31.5%, thus the structure stiffness has been significantly improved.

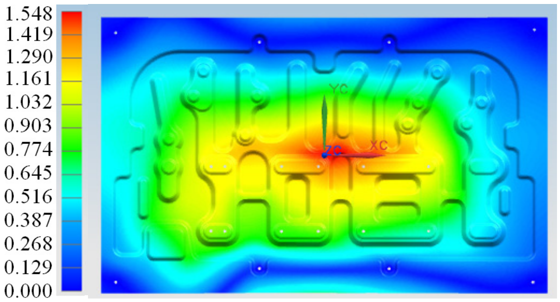


Fig. 4. Simulated cloud chart of deformation for the optimized design scheme.

## 3. CAE simulation of stamping process for the optimization design

In order to analyze the forming quality of the optimized design, numerical simulation of the stamping process is carried out by Dynaform5.7. The forming limit diagram (FLD) diagram is shown in Fig. 5, from which it is seen that no wrinkle or crack appears during the stamping process of the optimized design scheme. Although there occurs wrinkle and insufficient stretching on the flange region of the chassis, it has no influence on the product's quality since it will be cut off in the subsequent process. Fig. 6 illustrates the material's thinning ratio, in which the maximum thinning ratio is 28.2% and satisfies the industry requirement.

The prototype for the optimized design is manufactured to implement the verification test of structure stiffness as depicted in Fig. 7. It proves that no obvious dent is found while three people stand on the chassis' prototype for the optimized design, but severe deformation occurs even though one people stands on the chassis' prototype for the initial design. Therefore, structure stiffness of the optimized design is greatly improved and satisfies the requirement of the product.

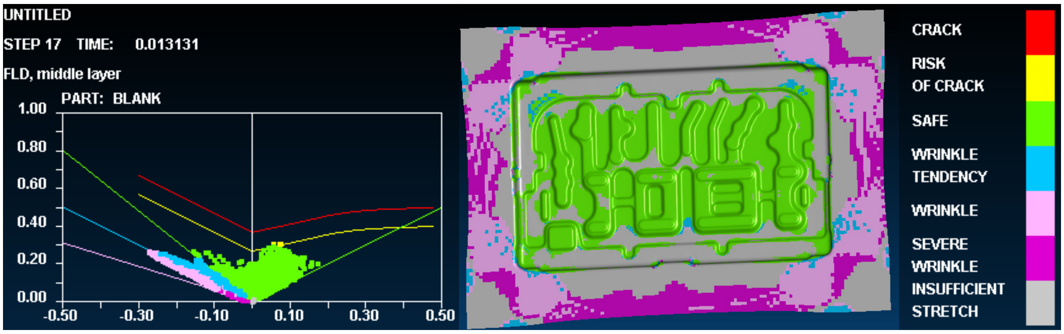


Fig. 5. FLD diagram of optimized design.

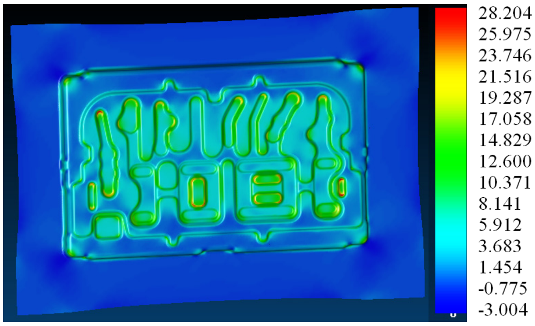


Fig. 6. Thinning ratio of the optimized design.

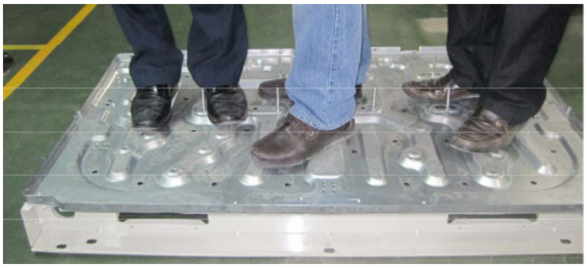

Fig. 7. Verification test of structure stiffness for prototype of optimized design.

## 4. Conclusion

In this paper, aiming at the structure stiffness of a certain air-conditioner's chassis, an integrated method of BP neural network and finite element simulation as well as orthogonal experiment is put forward. 1) CAE simulated results of structure stiffness are considered as the training data, whose number is determined by orthogonal experiment, and BP neural network model is established. 2) After training process, the reliability of trained BP neural network is verified by test data, and then the remained data sets of the comprehensive test are predicted by the trained neural network, thus the optimized data set can be obtained. 3) Numerical simulation is carried out for the optimized data set to investigate the forming quality. The simulation results illustrate that good forming quality has been gained without wrinkle or crack occurrence. 4) Finally, the prototype of chassis for the optimized design scheme is made, and verification test is implemented to examine the structure stiffness of the optimized scheme. It is proved that the structure stiffness for the optimized design scheme has been obviously improved, therefore it is feasible to adopt this method for structure optimization.

## Acknowledgements

This research is financially supported by the projects of China's National Ministry of Science and Technology (No. 2011IM020300) and Guangdong Province (No. 2011B061100001).

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